

IoT cloud integration with EfficientNet-B7 for real-time pest monitoring and leaf-based classification

Sabapathi Shanmugam, Vijayalakshmi Natarajan

Department of Computer Applications, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, India

Article Info

Article history:

Received Sep 29, 2024

Revised Jan 28, 2026

Accepted Feb 17, 2026

Keywords:

Detection

EfficientNet-B7

Machine learning

Prediction

YOLOv8

ABSTRACT

The increasing prevalence of pest infestations poses a significant threat to global agricultural productivity, often resulting in substantial yield losses and economic damage. To address this challenge, this paper proposes an intelligent, cloud-enabled pest detection and classification framework leveraging state-of-the-art deep learning techniques. The proposed system integrates YOLOv8 for rapid and accurate pest detection with EfficientNet-B7 for fine-grained species-level classification. The framework is trained and evaluated using the Pestopia dataset, which contains annotated images representing diverse pest species. To enhance data diversity, robustness, and model generalization, data augmentation techniques such as center cropping and horizontal flipping are applied during preprocessing. YOLOv8 is employed to detect and localize pest instances within images, while EfficientNet-B7 extracts high-level discriminative features from detected regions to enable precise species identification. Furthermore, the system incorporates cloud-based real-time monitoring through Adafruit IO, enabling scalable, remote access to pest information for timely decision-making. The performance of the proposed framework is evaluated using standard metrics, including accuracy, precision, recall, and F1-score, achieving values of 97.8%, 98.9%, 98.4%, and 98.9%, respectively. The experimental results demonstrate the effectiveness and reliability of the proposed approach for real-time pest management. The cloud-integrated architecture facilitates proactive pest control strategies, supporting smarter, data-driven agricultural practices, and improved crop protection.

This is an open access article under the [CC BY-SA](#) license.



Corresponding Author:

Sabapathi Shanmugam

Department of Computer Applications, SRM Institute of Science and Technology, Ramapuram Campus

Chennai, Tamil Nadu, India

Email: ss9771@srmist.edu.in

1. INTRODUCTION

The potential of agriculture sector to increase the demand of food and provide nutritional healthful meals is quite great. Farmers are struggling to manage the presence of agricultural insects in the field because of the pest attack and resulting devastation of a considerable part of crops and their quality [1]. Pest identification is an important agricultural issue because it impacts greatly on crop health, food security, and livelihoods of farmers. Pests can be very bad to crops and especially the small-scale farmers who cannot afford the resources to recover can be hit very hard and may reduce the yield and quality of crop drastically leading to huge losses of money. To manage infestations that are not noticed or identified in time, excessive pesticide dosage is often required causing environmental degradation, inflated costs of production, and pest resistance to pesticides. In addition, outbreak of pests may compromise affordability and availability of food, especially in regions where agriculture is a major source of food. The manual methods of pest monitoring are

not suitable in modern and large-scale farming activities, as they are time-consuming, labor-intensive, and they also subject to human error.

Pest infestations have a great influence on the agricultural production, that leads to the financial losses and threat of food security. The conventional techniques of pest identification are manual and can be very cumbersome, time-consuming, and subject to human error. The advent of the deep learning technology has made it possible to have automatic, accurate, and real-time pest detection systems in this industry. Convolutional neural networks (CNNs) are considered one type of deep learning model that has proven to be very successful in image-based tasks aimed at pest identification. Equally, the YOLO system improves the detection capability of pests and diseases, by adding adaptive spatial feature fusion, which boosts detection effectiveness without augmenting the computational expenses [2]-[5]. Such sophisticated architectures as the dilated multi-scale attention U-Net have been constructed to overcome problems that exist in the detection of pests of different shapes and sizes on complex backgrounds and have proved to be effective in the field. Furthermore, CNN-based models with attention mechanisms and recurrent units, including the convolutional slice-attention-based gated recurrent unit, have demonstrated great accuracy in the pest segmentation and classification tasks [6]-[9]. In this case, the most effective methodologies are EfficientNet, YOLO variations, and CNNs to use as intelligent pest detection and use classification systems. YOLOv8 enhances the detection speed and the detection accuracy, whereas CNNs extract relevant features of images. Scalable CNN EfficientNet-B7 uses depth, breadth, and resolution to optimize minuscule scale categorization. All these factors combine to assist in giving a viable solution to modern pest control in agriculture through the integration of real-time accessibility in clouds, precise classification, and rapid identification.

Combining deep learning with internet of things (IoT) devices, such systems help to collect and process data in real-time, and conduct interventions in time, and eliminate the need to use manual labor. The current project will focus on the creation of a detailed pest detection system that will utilize the latest DL models and IoT technologies to give precise, effective, and scalable solutions to the problem of modern agriculture [10]-[14]. The IoT is a network of multiple interconnected devices that are capable of collecting, transmitting, and storing information. The IoT is changing the way agricultural activities are done by enabling automated decision-making, data collection, and real-time monitoring. Remote sensing of pests will assist farmers in the discovery and management of pests.

The combination of the IoT devices and other technologies in the agricultural industry can help the modern farming practices to be more productive, have fewer manual interventions, proactive intervention, and based decision-making. The use of IoT has also made smart farming more popular as a means of delivering improved and cheaper food to the growing population of the world. Data can be applied, among other things, in smart farming to track the pests, decrease waste, and utilize the available space more efficiently [15]-[18]. The report suggests a system based on artificial intelligence (AI) which uses real-time data of the IoT devices, and advanced analytics to identify, prevent, and control pests to optimize precision agriculture activities [19]-[22]. To enhance sustainable farming, the essay will focus on how AI algorithms and remote sensing data may prove useful in offering real-time tracking, early detection, and correct forecasting of insect pests [23], [24]. In this paper, we are going to discuss statistical and deep learning models in different agricultural settings with a particular focus on the modes of predicting insect populations [25]-[27]. The purpose of the current work is to evaluate the extent to which smart farming may exploit AI technology to support farmers, agricultural organizations, and crop owners in evaluating and early identification of agricultural diseases and pests, and reducing interruptions to food production.

2. LITERATURE REVIEW

The importance of identifying pests in agriculture has a direct effect on crop output, food security, and economic stability. Traditional methods of pest surveillance, such as physical traps and manual scouting, are often time-consuming, labor-intensive, and prone to human error. To enhance accuracy, scalability, and efficiency, researchers have increasingly focused on automated pest detection systems that exploit computer vision, machine learning, and deep learning. Earlier approaches relied on classical image processing techniques using color, texture, and shape features, combined with traditional classifiers such as support vector machines (SVM) and K-nearest neighbors (K-NN). Although these methods were moderately effective, their performance was significantly affected by variations in illumination, noise levels, and insect morphology.

In the food production and processing industries, AI and machine learning technologies are increasingly employed to improve food quality and protect crops against insect attacks. One such pest that severely affects agricultural productivity is the fall armyworm (FAW). A FAW detection system based on mask region convolutional neural networks (Mask R-CNN) achieved a mean average precision of 94.21% [12]. Studies examining AI and IoT applications in cotton farming revealed that most systems focus on a limited number of pest species, neglecting predatory and immature insects due to their detection complexity

[13]. Unmanned aerial vehicle (UAV)-based approaches have been introduced to enhance pest detection, classification, and crop monitoring. By integrating YOLOv5s with multi-scale feature extraction, extended cross stage partial (CSP) modules, and attention mechanisms, accurate pest identification has been demonstrated in UAV scenarios [14]. Deep learning methods such as semantic segmentation and image classification have significantly improved pest and disease detection, along with object and change detection capabilities [15]. IoT-based intelligent pest detection systems with smart traps and integrated computing units have further enabled real-time monitoring in field conditions [16].

Continuous pest infestation detection in fruit orchards has been achieved using low-power embedded systems equipped with machine learning models and neural accelerators. Energy harvesting mechanisms significantly extend battery life in such deployments [17]. Additionally, parallel and distributed simulation frameworks (PDSF) integrated with IoT distribute computational loads across multiple GPUs, ensuring reliability and scalability for agricultural monitoring and pest control [18].

Despite significant progress, AI-driven pest detection systems face several limitations. Model performance heavily depends on large, well-annotated datasets, which remain scarce for rare, immature, or predatory insect species. Environmental variations such as extreme lighting, occlusion, and complex backgrounds can degrade real-world accuracy. UAV- and IoT-based solutions introduce challenges related to energy consumption, communication latency, and deployment costs. Furthermore, deploying deep learning models on low-power embedded devices remains computationally constrained. Addressing these issues requires improved dataset diversity, lightweight architectures, adaptive learning strategies, and cost-effective deployment solutions for sustainable agricultural adoption.

3. METHOD

This section presents the complete methodological framework adopted for predicting student academic. The initial phase of the proposed pest detection and classification system method is the utilization of the Pestopia dataset comprised of relevant pest images. There is a supplement of the data by use of center cropping and horizontal flipping in order to enhance the generalization of the models and augment the variety of the dataset. High-level representations of the pictures are then received after the augmentation process through feature extraction by EfficientNet. YOLOv8 is a real-time object detector that is installed in order to detect and identify pests in the images with accuracy. The identified areas are then classified under EfficientNet-B7, in order to distinguish various types of pests. Appropriate measures are used to measure performance in the model at the same time. Finally, the results of the detection are saved in the Adafruit IO cloud service which makes them accessible remotely and enables real-time monitoring.

3.1. Dataset image: pestopia

Pestopia is a large database of high-resolution photographs of 56,685 common Indian pests containing all the information about the insecticides commonly applied to control them. The dataset is supposed to assist the researchers and practitioners to design and improve machine learning algorithms to identify and manage pests. Also, it will be helpful to farmers and pest control experts who may want to know more about Indian pests and methods of controlling pests. The variety of pests in Pestopia presents an unparalleled opportunity to explore and review the complex world of Indian pest control.

3.2. Data augmentation

Data augmentation is the technique for creating new data artificially from the available data. It is mainly used to train new machine learning models. For the initial training of machine learning models, enough complex and large datasets are required. At the same time, due to issues related to data silos, legal barriers, and many others, finding enough diverse real-world datasets is difficult.

3.3. Feature extraction using EfficientNet

EfficientNet achieves high accuracy for small target objects, meeting all the needs of the research. EfficientNet consists of one stem and seven modules, as depicted in Figure 1. The stem network design employs convolutional layers to change the number of feature channels. Critical feature layers P3 through P5 are obtained by numerous mobile inverted bottleneck convolution (MBConv) layers of the network. Two subsampling methods yield deeper layers P6 and P7 with richer semantic features.

3.4. YOLOv8 module

Since its launch, the YOLO single-stage target identification technique has attracted considerable scholarly attention. The YOLO algorithm has been continuously improved and modified throughout time. With the introduction of YOLOv8, an algorithmic variation that ensures real-time performance with

enhanced detection accuracy and a lightweight network architecture, the Ultralytics team solidified its position as a well-liked approach in the target detection sector in 2023.

EfficientNet is definite mathematically in (1):

$$P = \sum_{x=1,2,\dots,n} M_x^{T_x}(y(A_x, B_x, C_x)) \quad (1)$$

where M_x – layer means and repeats T_x . Time variance of x . (A_x, B_x, D_x) represents the shape input in tensor of y concerning the layer x . The inputs of the images change from $256 \times 256 \times 3$ to $224 \times 224 \times 3$. To increase the model accuracy, the layers must scale with a proportional ratio optimized with the given formula, as shown in (2) and (3).

$$\max_{x,y,z} = ACC(P(x, y, z)) \quad (2)$$

$$P(x, y, z) = \sum_{s=1,2,\dots} M_s^{L_s}(Y_{(z,A_s,z,B_s,y,D_s)}) \quad (3)$$

The (2) uses x , y , and z to represent height, width, and resolution. The number of model layers and parameter details are displayed in (3). Figure 2 shows a systematic diagram of EfficientNet-B7.

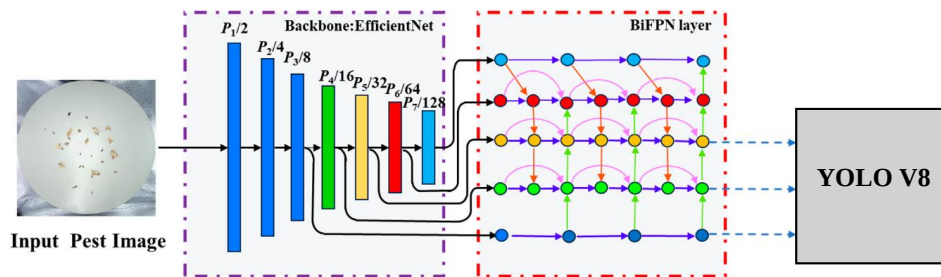


Figure 1. Efficient net module

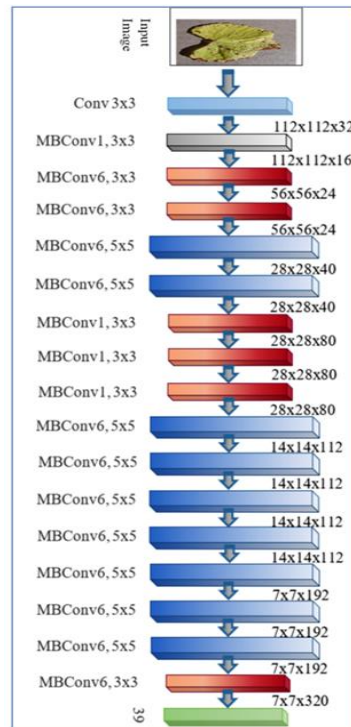


Figure 2. Architecture of EfficientNet-B7

4. RESULT AND DISCUSSION

The deep neural network (DNN) used in this study is deliberately designed as a compact yet expressive. In this research, the analysis of accurate detection of plant pests using the efficient model of EfficientNet-B7 has been conducted. In addition to that, a well-planned training and validation procedure for accurate image analysis has been used in the study. The pest image dataset, which included real-life agricultural field images, has been manually labeled. This contained 5,000 images of 12 pest types. Out of which, 3,500 images for training (70%), 750 images for validation (15%), and another 750 images for testing (15%) were used. The image preprocessing took place using the OpenCV-Python3 library, which performed a number of operations like resizing all input images with a size of 600×600 pixels, normalized input pixels in between 0 to 1, and consistency in colors (RGB normalizing). In order to increase the efficiency of the model with better generalization capabilities, a data augmentation procedure has been adopted using Keras-GPU. This contained horizontal flipping with a probability of 50% for images, center cropping (100%), adjustment of brightness and contrast (20% probability), rotation for angles of $\pm 15^\circ$ for 30% images, and a minor zoom of (0.1x to 1.2x) for images.

The Pestopia dataset originally contains 56,685 images. Each image was subjected to center cropping and horizontal flipping techniques in order to enrich the dataset, thereby doubling its size to 113,370 images. Figure 3 illustrates this augmentation procedure. Figure 4 illustrates that the suggested technique employed a 0.5 confidence level for both species' classification and object detection. The YOLOv8 detections with confidence scores lower than 0.5 were ignored in order to reduce false positives. Likewise, in the EfficientNet-B7 classification stage, whose predictions are below the threshold of 0.5, either had low confidence or were excluded, with class labels assigned based on the highest softmax probability. Accuracy analysis is shown in Figure 5. The training and validation loss values obtained using the EfficientNet-B7 model on the pestopia dataset are based on the number of pests on leaves, as depicted in Figure 6.



Figure 3. Augmentation (centre cropping and horizontal flipping)

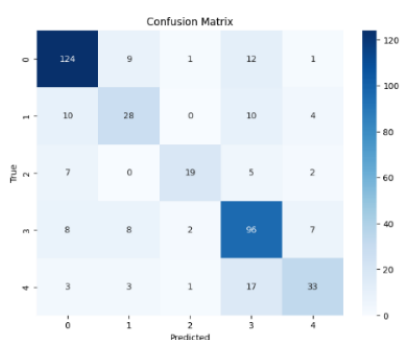


Figure 4. Confusion matrix for prediction of each class

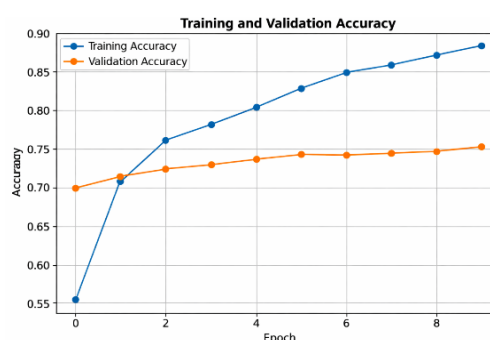


Figure 5. Accuracy of pest prediction

Figure 7 shows the various comparison results of the metrics used in the work. Figures 8 and 9 below is a representation of the mean absolute error (MAE) and mean squared error (MSE) of the EfficientNet model, which shows graphically how well or poorly the model is performing in making predictions in pest detection. Long loss curve of the work is shown in Figure 10.

The effectiveness of EfficientNet-B7's architecture in the pest classification task is shown in Figure 11 which evaluates four key parameters: accuracy, precision, recall, and F1-score. These metrics give

a thorough assessment of the model's capability in detecting and classifying pests. The major pest groups are asiatic rice borer, yellow rice borer, paddy stem maggot, rice leaf roller, and rice leaf caterpillar, which are considered for evaluation in this method. It is apparent from the assessment that the model is performing exceptionally on all parameters of performance, thereby establishing its remarkable classification abilities.



Figure 6. Losses of pest prediction

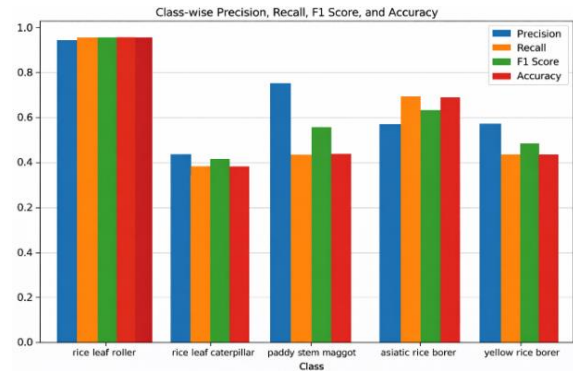


Figure 7. Performance metrics in pest prediction

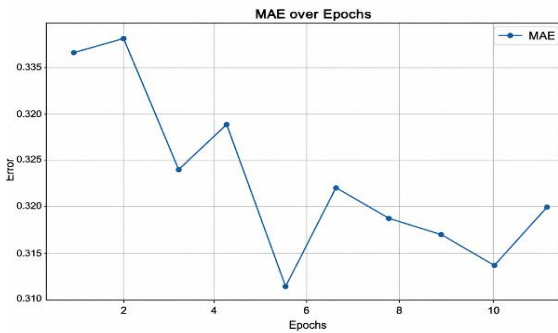


Figure 8. MAE curve over epochs

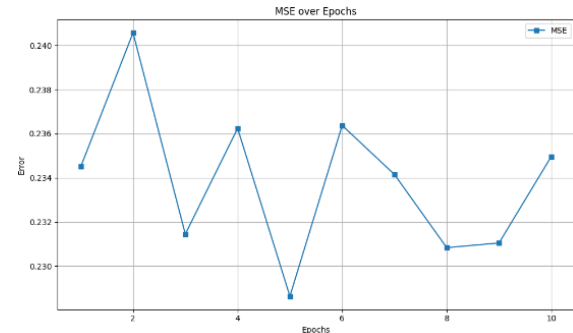


Figure 9. MSE curve over epochs

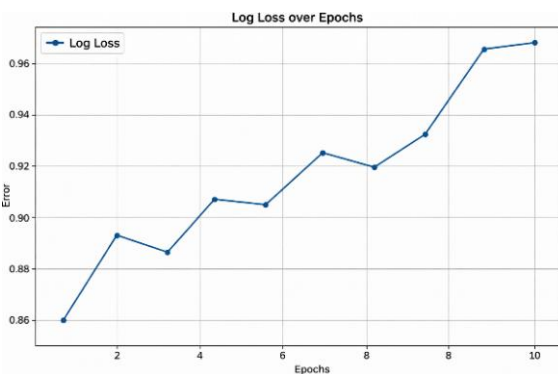


Figure 10. Log Loss curve over epochs

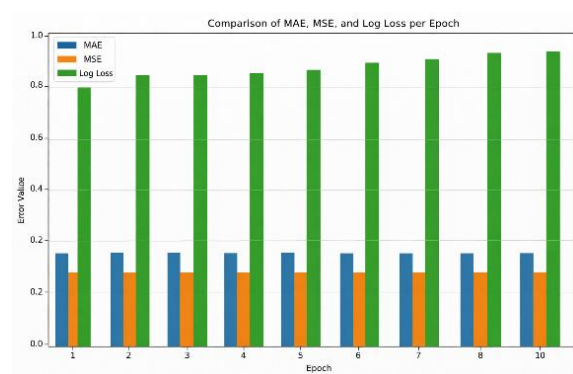


Figure 11. Comparison of MAE, MSE, and Log Loss per each epoch

This visual enables the observation of the error processes of each class. This information indicates the model's convergence process and the consistency of the model. The MAE value is considered low when it is below a certain threshold. From Figure 12, the multiclass pest detection receiver operating characteristic (ROC) curves indicate how well the EfficientNet model classifies over time. The graphs display information about how well the model discriminates between every class of pest during the course of training as in Figure 13.

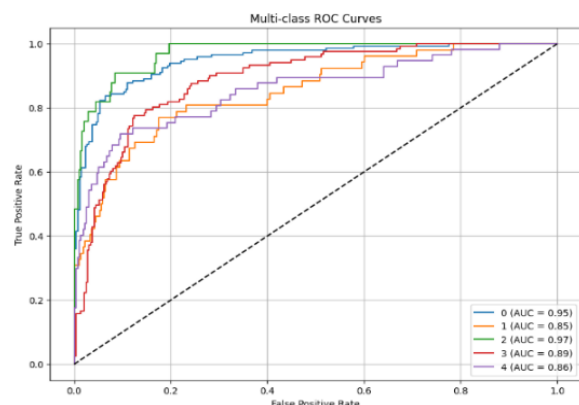


Figure 12. ROC curves (One-vs-Rest) for multiclass

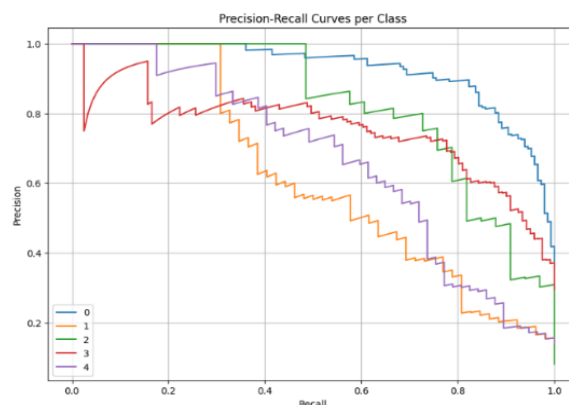


Figure 13. Precision-recall curves (per class)

The performance of the classification process for pest detection based on leaf images through the EfficientNet-B7 technique is represented in Figure 14, which depicts the normalized confusion matrix. This matrix highlights the prediction accuracy of the different classes in a normalized way, as well as the normalized frequency of predictions.

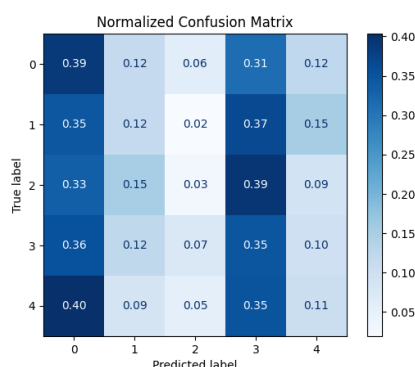


Figure 14. Normalized confusion matrix

5. CONCLUSION

The proposed pest detection and classification system in this study proves to accomplish an effective and complete approach to pest monitoring in modern agriculture. By utilising and improving the Pestopia dataset by means of strategic data augmentation methods, this proposed system ensures better overall generalization for different pest species and conditions. In addition to this, by combining EfficientNet for feature extraction and EfficientNet-B7 for pest classification, this proposed system ensures high precision and computational speed that is highly relevant in real-time agricultural applications. Moreover, YOLOv8 enhances its proposed system by ensuring rapid and accurate pest object detection suitable for utilisation in dynamic agricultural field conditions. By means of a series of standard tests, its efficiency and effectiveness for pest species classification is verified by ensuring precision, recall, F1-score, and accuracy values more than 80%. Moreover, the real-time upload of results of detections to the Adafruit IO cloud service increases the real-world functionality of the system. In general, the system developed is a scalable and automatic means of educating and enabling farmers and other stakeholders in agriculture on time about pest occurrences.

The system also has several problems despite its encouraging results. Further optimization of the developed model, through techniques such as pruning and quantization, to enable the use of low-power edge devices for in-real-life pest species monitoring, is also one of the plans as part of future work. Enhancing the system's usability by using multilingual interfaces and automated alerts for farmers regarding pest species will also be considered, along with plans to make the system more accurate using multimodal input such as weather and soil information for enhanced pest species prediction.

ACKNOWLEDGMENTS

The authors would like to acknowledge the support and resources provided by the Department of Computer Applications, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, India.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Sabapathi Shanmugam	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Vijayalakshmi Natarajan		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

- [1] T. Kasinathan, D. Singaraju, and S. R. Uyyala, "Insect classification and detection in field crops using modern machine learning techniques," *Information Processing in Agriculture*, vol. 8, no. 3, pp. 446–457, Sep. 2021, doi: 10.1016/j.inpa.2020.09.006.
- [2] L. Du, J. Zhu, M. Liu, and L. Wang, "YOLOv7-PSAFP: Crop pest and disease detection based on improved YOLOv7," *IET Image Processing*, vol. 19, no. 1, Jan. 2025, doi: 10.1049/ipr2.13304.
- [3] Y. Yuan, J. Sun, and Q. Zhang, "An Enhanced Deep Learning Model for Effective Crop Pest and Disease Detection," *Journal of Imaging*, vol. 10, no. 11, p. 279, Nov. 2024, doi: 10.3390/jimaging10110279.
- [4] A. Khan, S. J. Malebary, L. M. Dang, F. Binzagr, H. K. Song, and H. Moon, "AI-Enabled Crop Management Framework for Pest Detection Using Visual Sensor Data," *Plants*, vol. 13, no. 5, p. 653, Feb. 2024, doi: 10.3390/plants13050653.
- [5] B. Cardoso, C. Silva, J. Costa, and B. Ribeiro, "Internet of Things Meets Computer Vision to Make an Intelligent Pest Monitoring Network," *Applied Sciences*, vol. 12, no. 18, p. 9397, Sep. 2022, doi: 10.3390/app12189397.
- [6] S. Azfar *et al.*, "An IoT-Based System for Efficient Detection of Cotton Pest," *Applied Sciences (Switzerland)*, vol. 13, no. 5, p. 2921, Feb. 2023, doi: 10.3390/app13052921.
- [7] D. Aziz *et al.*, "Remote sensing and artificial intelligence: revolutionizing pest management in agriculture," *Frontiers in Sustainable Food Systems*, vol. 9, Feb. 2025, doi: 10.3389/fsufs.2025.1551460.
- [8] D. Kapetas, P. Christakakis, S. Faliagka, N. Katsoulas, and E. M. Pechlivani, "AI-Driven Insect Detection, Real-Time Monitoring, and Population Forecasting in Greenhouses," *AgriEngineering*, vol. 7, no. 2, p. 29, Jan. 2025, doi: 10.3390/agriengineering7020029.
- [9] T. N. Hashem, J. M. M. Joudeh, and A. M. Zamil, "Smart Farming (AI-Generated) as an Approach to Better Control Pest and Disease Detection in Agriculture: POV Agricultural Institutions," *Migration Letters*, vol. 21, no. S1, pp. 529–547, Dec. 2023, doi: 10.59670/ml.v21is1.6178.
- [10] B. Prasath and M. Akila, "IoT-based pest detection and classification using deep features with enhanced deep learning strategies," *Engineering Applications of Artificial Intelligence*, vol. 121, p. 105985, May 2023, doi: 10.1016/j.engappai.2023.105985.
- [11] S. Qazi, B. A. Khawaja, and Q. U. Farooq, "IoT-Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review, Current Challenges and Future Trends," *IEEE Access*, vol. 10, pp. 21219–21235, 2022, doi: 10.1109/ACCESS.2022.3152544.
- [12] T. Kasinathan and S. R. Uyyala, "Detection of fall armyworm (spodoptera frugiperda) in field crops based on mask R-CNN," *Signal, Image and Video Processing*, vol. 17, no. 6, pp. 2689–2695, Sep. 2023, doi: 10.1007/s11760-023-02485-3.
- [13] D. O. Kiobia, C. J. Mwitwa, K. G. Fue, J. M. Schmidt, D. G. Riley, and G. C. Rains, "A Review of Successes and Impeding Challenges of IoT-Based Insect Pest Detection Systems for Estimating Agroecosystem Health and Productivity of Cotton," *Sensors*, vol. 23, no. 8, p. 4127, Apr. 2023, doi: 10.3390/s23084127.
- [14] R. K. Ray, S. Chakravarty, S. Dash, S. N. Mohanty, and J. V. N. Ramesh, "An interactive AI-based crop and pest management system leveraging transfer learning for enhanced sustainable agriculture," *Modeling Earth Systems and Environment*, vol. 11, p.

IoT cloud integration with EfficientNet-B7 for real-time pest monitoring and leaf ... (Sabapathi Shanmugam)

- 244, 2025, doi: 10.1007/s40808-025-02445-5.
- [15] S. Wang *et al.*, “Advances in Deep Learning Applications for Plant Disease and Pest Detection: A Review,” *Remote Sensing*, vol. 17, no. 4, p. 698, Feb. 2025, doi: 10.3390/rs17040698.
 - [16] S. Ahmed *et al.*, “IoT based intelligent pest management system for precision agriculture,” *Scientific Reports*, vol. 14, no. 1, p. 31917, Dec. 2024, doi: 10.1038/s41598-024-83012-3.
 - [17] A. Albanese, M. Nardello, and D. Brunelli, “Automated Pest Detection with DNN on the Edge for Precision Agriculture,” *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 11, no. 3, pp. 458–467, Sep. 2021, doi: 10.1109/JETCAS.2021.3101740.
 - [18] M. G. Nayagam, B. Vijayalakshmi, K. Somasundaram, M. A. Mukunthan, C. A. Yogaraja, and P. Partheeban, “Control of pests and diseases in plants using IOT Technology,” *Measurement: Sensors*, vol. 26, p. 100713, Apr. 2023, doi: 10.1016/j.measen.2023.100713.
 - [19] M. A. Ali, R. K. Dhanaraj, and A. Nayyar, “A high performance-oriented AI-enabled IoT-based pest detection system using sound analytics in large agricultural field,” *Microprocessors and Microsystems*, vol. 103, p. 104946, Nov. 2023, doi: 10.1016/j.micpro.2023.104946.
 - [20] A. Passias *et al.*, “Insect Pest Trap Development and DL-Based Pest Detection: A Comprehensive Review,” *IEEE Transactions on AgriFood Electronics*, vol. 2, no. 2, pp. 323–334, Sep. 2024, doi: 10.1109/tafe.2024.3436470.
 - [21] P. Christakakis *et al.*, “Smartphone-Based Citizen Science Tool for Plant Disease and Insect Pest Detection Using Artificial Intelligence,” *Technologies*, vol. 12, no. 7, p. 101, Jul. 2024, doi: 10.3390/technologies12070101.
 - [22] D. Sheema, K. Ramesh, V. K. Reshma, and R. Surendiran, “The Detection and Identification of Pest-FAW Infestation in Maize Crops Using Iot-Based Deep-Learning Algorithms,” *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 12, pp. 180–188, Dec. 2022, doi: 10.14445/23488379/IJEEE-V9I12P116.
 - [23] M. A. Ali, A. K. Sharma, and R. K. Dhanaraj, “Multi-Features and Multi-Deep Learning Networks to identify, prevent and control pests in tremendous farm fields combining IoT and pests sound analysis,” *Research Square*, Apr. 2024, doi: 10.21203/rs.3.rs-4290726/v1.
 - [24] E. V. Madhuri *et al.*, “Transforming Pest Management with Artificial Intelligence Technologies: The Future of Crop Protection,” *Journal of Crop Health*, vol. 77, no. 2, p. 48, Apr. 2025, doi: 10.1007/s10343-025-01109-9.
 - [25] M. Suguna, D. Prakash, C. U. O. Kumar, M. Revathi, and R. K. Dhanaraj, “AI-based pest detection and recovery model for cyber-physical agricultural systems,” *Agri 4.0 and the Future of Cyber-Physical Agricultural Systems*, Elsevier, pp. 237–256, 2024, doi: 10.1016/B978-0-443-13185-1.00013-7.
 - [26] A. B. Kathole, K. N. Vhatkar, and S. D. Patil, “IoT-Enabled Pest Identification and Classification with New Meta-Heuristic-Based Deep Learning Framework,” *Cybernetics and Systems*, vol. 55, no. 2, pp. 380–408, Feb. 2024, doi: 10.1080/01969722.2022.2122001.
 - [27] M. Mittal, V. Gupta, M. Aamash, and T. Upadhyay, “Machine learning for pest detection and infestation prediction: A comprehensive review,” *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 14, no. 5, Sep. 2024, doi: 10.1002/widm.1551.

BIOGRAPHIES OF AUTHORS



Sabapathi Shanmugam    holds an MCA degree and a B.Sc. in Computer Science. He has qualified both the National Eligibility Test (NET) and the State Eligibility Test (SET). He is currently pursuing a Ph.D. in Computer Science at SRM Institute of Science and Technology (SRMIST), Ramapuram Campus. His primary research interests include deep learning and the internet of things (IoT). He has published Scopus-indexed research articles on deep learning-based pest detection and classification in agriculture. His academic interests also include intelligent systems and applied machine learning. He can be contacted at email: ss9771@srmist.edu.in.



Dr. Vijayalakshmi Natarajan    is an Assistant Professor in the Department of Computer Applications at SRM Institute of Science and Technology. She received her Ph.D. in Computer Science from Anna University in 2018. She is an active member of various professional bodies, including the Computer Society of India (CSI) and the International Association of Engineers (IAENG). Additionally, she serves on the Board of Studies at Pondicherry University as a nominee. She has numerous publications in international journals, reflecting her dedication to research and academia. She can be contacted at email: vijayaln@srmist.edu.in.